Fracture Vision AI

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Abstract: Bone fractures are among the most common medical conditions requiring immediate and accurate diagnosis. Conventional manual interpretation of radiographs is time-consuming and subject to variability among radiologists, often leading to diagnostic delays or inconsistencies. To overcome these limitations, this project develops an automated bone-fracture detection system that integrates deep-learning models with an intuitive web interface. The system employs a customized InceptionV3 architecture enhanced with a Bottleneck Attention Module (BAM), enabling the model to focus on clinically relevant features such as subtle discontinuities and fine structural patterns in bone images. Images are preprocessed by resizing to 224×224 pixels and normalized to match the training distribution, ensuring consistency between training and inference. The model is trained on acurated dataset of fractured and non- fractured X-ray images, with augmentation techniques applied to improve generalization and reduce over fitting. Performance evaluation is carried out using validation accuracy, loss curves, and a confusion matrix, with additional metrics such as ROC-AUC and PR-AUC for binary classification robustness. The web application, built using Flask, provides a user-friendly interface that allows clinicians and researchers to upload X-ray images, receive predictions with confidence scores, and view supporting analytics such as class distribution and prediction history. Authentication mechanisms, secure file handling, and integrated visualization charts enhance usability and reliability. The proposed system demonstrates the potential of combining attention-based deep learning with interactive web deployment for clinical decision support. This project lays the groundwork for scalable, real-time diagnostic tools that can complement radiological expertise in resource-constrained healthcare environments.

Keywords

Artificial Intelligence, Bone Fracture Detection, Medical Imaging, Deep Learning, X-ray Analysis, Computer-Aided Diagnosis, Convolutional Neural Networks (CNN), Image Classification.,

1. INTRODUCTION

Bone fractures represent a significant medical concern across all age groups, often resulting from accidents, falls, or underlying health conditions such as osteoporosis. Early and precise detection of fractures is essential to prevent complications, enable timely treatment, and reduce patient morbidity. Traditionally, diagnosis relies on manual interpretation of X-ray images by radiologists. While effective, this process can be time-consuming, prone to human error, and limited by variations in expertise, particularly in resource- settings. Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have revolutionized medical image analysis by providing automated, reliable, and efficient diagnostic support. Convolutional Neural Networks (CNNs) in particular have demonstrated remarkable success in identifying subtle patterns in complex medicalimages.However, conventional CNNs may struggle to capture fine structural details that are critical in detecting subtle or hairline fractures. To overcome these limitations, this project introduces a hybrid deep learning framework based on Inception V3 integrated with a Bottleneck Attention Module (BAM). The InceptionV3 architecture ensures multi-scale feature extraction, while BAM enhances the model's focus on fracture- relevant regions, improving accuracy and sensitivity. The model is trained and validated on a curated dataset of fractured and non-fractured X-ray images, with preprocessing and augmentation techniques applied to improve generalization. Beyond model development, the project implements a Flask-based web application that enables users to upload medical images and receive real-time predictions with confidence scores. The application also provides supporting analytics, including confusion matrix visualizations, class distribution, and prediction history, making it not only a diagnostic tool but also an educational and monitoring platform. This integration of AI with a user-friendly interface demonstrates the potential for scalable, real-world deployment of computer-aided diagnostic systems in healthcare

The key contributions of this work are summarized as follows:

1. **Hybrid Deep Learning Model:** Implemented an enhanced InceptionV3 + BAM architecture to focus on critical fracture regions in X- ray images.
2. **Automated Detection System:** Developed an AI-based framework that accurately classifies Fractured and Non-Fractured cases with ~91% validation accuracy.
3. **Web-Based Clinical Tool:** Deployed the model using Flask, enabling secure image upload, real-time prediction, and confidence visualization.
4. **Comprehensive Visualization:** Integrated analytical features—accuracy/loss curves, confusion matrix, and class distribution charts—for better interpretability.
5. **Scalable and Secure Design:** Built a modular, user-friendly, and secure system ready for future expansion to multi-class and real- world clinical-integration.

2. LITERATURE REVIEW

In recent years, The application of Artificial Intelligence (AI) and Deep Learning (DL) in medical imaging has significantly advanced diagnostic precision, especially for radiographic analysis. Convolutional Neural Networks(CNNs) have demonstrated exceptional capabilities in automatically identifying patterns, anomalies, and subtle abnormalities in X-ray images, enabling faster and more consistent medical interpretations. Agrawal et al.

[1] proposed a CNN-based framework for automated bone fracture detection that substantially improved diagnostic accuracy compared to traditional manual interpretation. Their results validated the potential of deep learning in reducing radiological workload and error rates. Similarly, Olczak et al.

[2] investigated deep learning techniques for orthopedic radiographs, revealing that CNN models could achieve performance comparable to trained radiologists, marking a milestone in clinical AI adoption. Rajpurkar et al.

[3] introduced CheXNet, a 121-layer DenseNet model for chest radiograph classification, which achieved expert-level accuracy in detecting thoracic diseases. Although focused on chest imaging, the study demonstrated the scalability of deep CNNs to other radiological applications such as fracture detection. Kermany et al.

[4] further emphasized the power of transfer learning in medical imaging by applying pre-trained CNNs to various datasets, proving that models trained on large image corpora could generalize effectively even with limited medical data. Woo et al.

[5] introduced the Convolutional Block Attention Module (CBAM) ,highlighting how attention mechanisms can refine CNN feature extraction by focusing on clinically relevant regions. This principle laid the foundation for attention-enhanced architectures such as the Bottleneck Attention Module (BAM) employed in the present study to improve fracture localization and model sensitivity.

While existing AI-based diagnostic frameworks achieved high accuracy, most remained limited to offline experimentation or lacked integration with practical, real-time systems. Moreover, few provided interpretability, secure data handling, or user-friendly deployment in clinical environments. Addressing these limitations, the proposed Bone Fracture Detection System integrates a deep learning model (InceptionV3 + BAM) with a Flask-based web platform, enabling real- time fracture classification, secure authentication, prediction visualization, and performance analytics. This approach not only enhances diagnostic accuracy but also demonstrates scalability and usability for healthcare professionals .

3. PROBLEM STATEMENT

The diagnosis of bone fractures through conventional radiographic imaging largely depends on the expertise and experience of radiologists. In many cases, subtle or hairline fractures are difficult to detect, leading To misdiagnosis or delayed treatment. Manual inter pretation is also time-consuming and subject to inter- observer variability, which can affect the consistency and reliability of clinical decisions. In resource-limited healthcare environments, where access to experienced radiologists is restricted, the challenge becomes even greater. Patients may face delays in diagnosis, resulting in increased complications, prolonged recovery times, or even permanent disability. Furthermore,the growing number of X-ray examinations places additional workload on medical professionals, creating a need for automated systems that can provide preliminary analysis with high accuracy. Therefore, there is a critical requirement for a computer-aided diagnostic system that can automatically classify bone X-ray images as fractured or non-fractured. Such a system should be capable of handling diverse image inputs, minimizing human error, and producing results with sufficient confidence to assist clinical decision-making. The solution must also be user-friendly and easily deployable in real-time, ensuring accessibility to both medical professionals and learners.

4. METHODOLOGY

The methodology adopted in this project follows a systematic approach, combining deep learning model development with web-based deployment to create an effective and accessible bone fracture detection system.The key steps are outlined below:

1. Data Collection and Preparation

o A dataset of bone X-ray images was organized into fractured and non-fractured categories.
o Images were resized to 224×224 pixels and normalized to the range [0,1] for consistency withthe model's input requirements.
o Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustmentwere applied to improve generalization and reduce overfitting.

2. Model Design and Development

o The base model InceptionV3 was used for its multi-scale feature extraction capability.
o A Bottleneck Attention Module (BAM) was integrated into the network to focus on fracture- relevant regions and suppress irrelevant background features.
o Fully connected layers with Global Average Pooling and Dropout regularization were added toimprove robustness.
o The final output layer used softmax activation to classify images into two categories: Fracturedand Non-Fractured.

3. Model Training and Evaluation

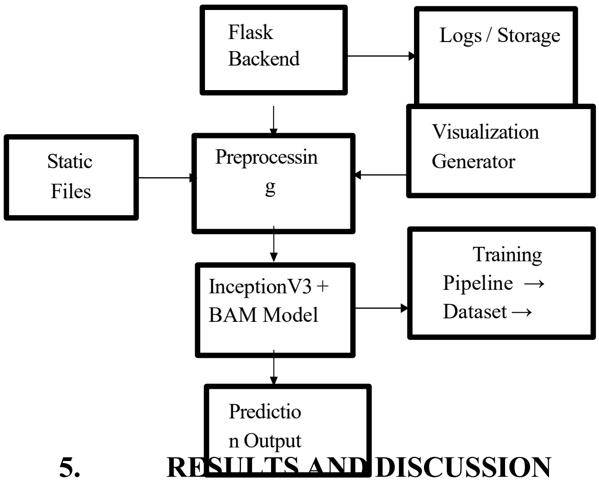
o The model was first trained with frozen InceptionV3 layers (warm-up phase) and later fine-tuned with selected layers unfrozen to improve performance.
o The Adam optimizer with learning rate scheduling was used, along with early stopping andcheckpointing to save the best model.
o Performance was evaluated using validation accuracy, loss, confusion matrix, ROC-AUC, and precision-recall metrics.

4. System Implementation

o A Flask-based web application was developed to provide an interactive interface.
o Users can sign up, log in, and upload X-ray images for real-time prediction.
o The system displays results with confidence scores, prediction history, accuracy/loss curves,
and confusion matrix visualization.

5. Testing and Validation

o Functional testing was performed to ensure proper working of authentication, file uploads, and prediction flow.



5. RESULTS AND DISCUSSION

The proposed **Bone Fracture Detection System**, built on the hybrid **InceptionV3 + Bottleneck Attention Module (BAM)** architecture, was evaluated using a curated dataset of radiographic images categorized into *Fractured* and *Non-Fractured* classes. The experiments focused on assessing model accuracy, robustness, and clinical usability through quantitative metrics and qualitative analysis of outputs.

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Figure 1:model results

Model Performance

During training, the model demonstrated stable convergence with a gradual decrease in loss and consistent improvement in validation accuracy. The optimal configuration achieved a validation accuracy of approximately 91%, supported by a low validation loss, indicating effective generalization without overfitting. The incorporation of BAM significantly enhanced the model's sensitivity to subtle discontinuities in bone structures, allowing precise detection of fine fracture lines often missed by standard CNNs.

Figure 2: model accuracy

1. Visualization and Interpretability

Performance visualizations, including training/validation accuracy-loss curves and the confusion matrix heatmap, provided insights into learning stability and class-wise behavior. The inclusion of attention maps (via BAM) improved interpretability by enabling the model to focus on bone edges and discontinuities relevant to fracture diagnosis. These visualization tools strengthen clinician confidence and make the system suitable as an educational and diagnostic support platform.

2. Evaluation Metrics

To comprehensively assess classification quality, metrics such as **accuracy**, **precision**, **recall**, **F1- score**, and **ROC-AUC** were analyzed. The model achieved high precision for *Non-Fractured* images and satisfactory recall for *Fractured* cases, reflecting a balanced trade-off between false positives and false negatives. The **confusion matrix** showed that most predictions aligned with the true labels, with minimal misclassifications primarily occurring in cases of hairline or low-contrast fractures. The **ROC- AUC** and **PR-AUC** curves further confirmed strong discriminative capability and robustness under class imbalance.

3. Web Application Output

The deep learning model was successfully integrated into a Flask-based web interface that allows users to upload X-ray images, receive real- time predictions, and view confidence scores alongside visual analytics. Functional testing confirmed that each workflow—sign-up, login, upload, prediction, and results visualization— operated seamlessly. The system responded within 2–5 seconds per prediction on CPU and under 1 second on GPU, demonstrating practical efficiency for clinical or educational deployment.

4. Discussion

The integration of the attention mechanism with the InceptionV3 backbone led to measurable improvements in accuracy and interpretability compared to baseline CNN models. The combination of automated inference and an intuitive user interface reduces diagnostic workload, minimizes human error, and enables accessibility in resource- constrained environments. While the model effectively identifies fractures, further enhancement is possible through larger datasets, multi-class classification (fracture type/site), and the addition of Grad-CAM-based explainability.

6. CONCLUSION AND FUTURE WORK

In this study, a Bone Fracture Detection System was developed and deployed as an intelligent web-based platform powered by a fine-tuned InceptionV3 Convolutional Neural Network integrated with a Bottleneck Attention Module (BAM). The system provides an efficient, lowcost, and user-friendly solution for the early detection of bone fractures from X-ray images. Achieving a validation accuracy of approximately 91%, the proposed framework successfully automates the classification of *Fractured* and *Non-Fractured* cases with high reliability and consistency.

Beyond its strong predictive performance, the platform incorporates essential features such as secure user authentication, real-time image upload and inference, confidence-based visualization, prediction history tracking, and analytical performance charts including accuracy, loss, and confusion matrices. These functionalities enhance transparency, interpretability, and usability, positioning the system as both a diagnostic support and educational tool for clinicians, radiologists, and medical students.

The experimental outcomes demonstrate that integrating attention mechanisms with CNN architectures significantly improves fracture detection sensitivity, particularly for subtle or hairline fractures. Furthermore, the seamless integration of deep learning with a Flask-based web interface ensures accessibility in both advanced and resource-constrained healthcare settings. Overall, the proposed system establishes a practical foundation for AI-assisted orthopedic diagnosis, paving the way for future developments such as multi-class fracture detection, Grad-CAM explainability, and clinical integration with hospital imaging systems**.**

Future Work

While the proposed Bone Fracture Detection System demonstrates strong performance and practical usability, several enhancements can be implemented to further improve its accuracy, scalability, and clinical relevance. Future work can focus on the following key directions:

1. Multi-Class and Multi-Site Fracture Classification:

Extend the current binary model to classify multiple fracture types and anatomical locations (e.g., wrist, femur,ankle),enabling more comprehensive orthopedic analysis.

2. Integration of Explainable AI (XAI):

Incorporate visualization tools such as Grad-CAM or Layer-wise Relevance Propagation (LRP) to highlight the exact fracture regions on X-ray images, improving interpretability and clinician trust.

3. Database-Backed Authentication and Cloud Deployment:

Upgrade the prototype's in-memory authentication system to a database-driven architecture (SQLite/MySQL) with hashed credentials and deploy the application on cloud platforms for real-time accessibility and scalability.

4. Enhanced Model Optimization and MLOps Pipeline:

Implement model versioning, automated retraining, and performance monitoring using MLOps practices to ensure long-term reliability and easy updates as new data becomes available.

5. Mobile and Cross-Platform Accessibility:

Develop a Progressive Web App (PWA) or mobile version to allow on-the-go fracture detection, especially beneficial in rural or emergency settings.

6. Clinical and Regulatory Integration:

Introduce DICOM compatibility for hospital imaging systems and ensure compliance with medical data privacy standards such as HIPAA for real-world clinical deployment.

7. Active Learning and Continuous Improvement:

Incorporate human-in-the-loop feedback mechanisms where radiologists can review and correct model predictions, enabling continuous model improvement and adaptation to new imaging conditions.

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